

# Pollen Identification Using Neural Networks

Performance of different neural network architectures in Identifying Pollen based on images. Feature extraction using Classifynder and new approaches using convolutional neural Networks are tested.

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## ABSTRACT

Traditional morphological methods for pollen identification in Quaternary palaeoecology are time consuming and can be limited in taxonomic precision. The automated Classifynder system (CFS; Holt et al. 2011) has the potential to use detailed morphological measurements and machine learning techniques to distinguish pollen types at higher levels of taxonomic resolution. In addition convolutional neural networks (CNNs) are powerful tools in classifying images. These approaches open new and exciting prospects for the classification of pollen.



Classifynder System.  
Image Source: <http://www.museum.ac.uk/resources/files/News%20Items/2016/Classifynder-ecsp.jpg>

## Classification Results

Classifier	E. frax.	E. pauc.	E. p. niph.	E. stell.	Acc.
Classifynder	65%	46%	73%	64%	62%
R. Forest	63%	50%	69%	70%	63%
h2o	75%	51%	70%	59%	64%
LeNet	69%	70%	69%	72%	70%
Resnet	66%	70%	64%	77%	69%
Inception bn	76%	73%	71%	80%	75%

## Results

Overall the CNNs performed better than the classifications based on the Classifynder extracted morphology data. Accuracy was higher when comparing species as well as total accuracy.

## Methods & Materials

The automated CFS was used to gather 2700 images and morphological information of 4 Eucalyptus pollen species collected from the Herbarium Collection at Kew, London. I have tested several classification methods on the dataset, by comparing the performance of the CFS to random forest and different CNNs. LeNet (Lecun et al. 1998) was developed for written character recognition, while Resnet (He et al. 2016) and Inception bn (Ioffe et al. 2015) were developed for image classification.

During classification the dataset was split into a 70% training and a 15% validation and test set. The images were scaled to 28x28 pixels.

## Confusion matrices

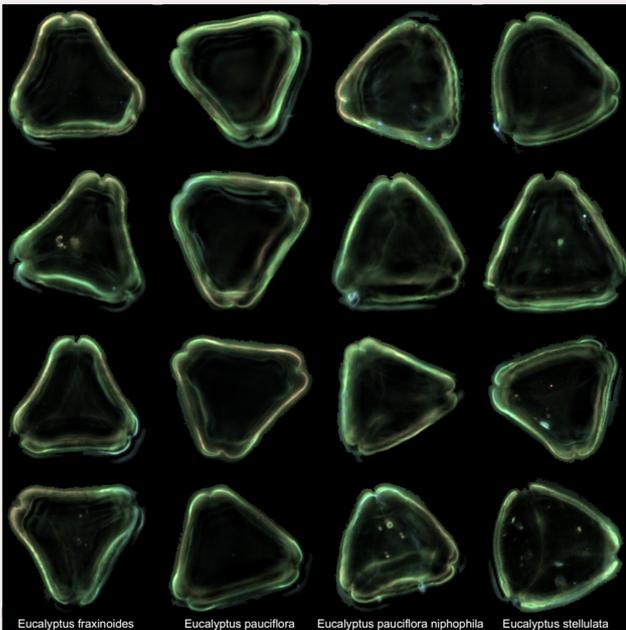
Classifier	E. frax.	E. pauc.	E. p. niph.	E. stell.	Recall
Classifynder	60	10	12	11	65%
E. frax.	7	41	27	14	46%
E. pauc.	6	10	90	18	73%
E. p. niph.	6	13	16	64	64%
E. stell.	6	13	16	64	64%

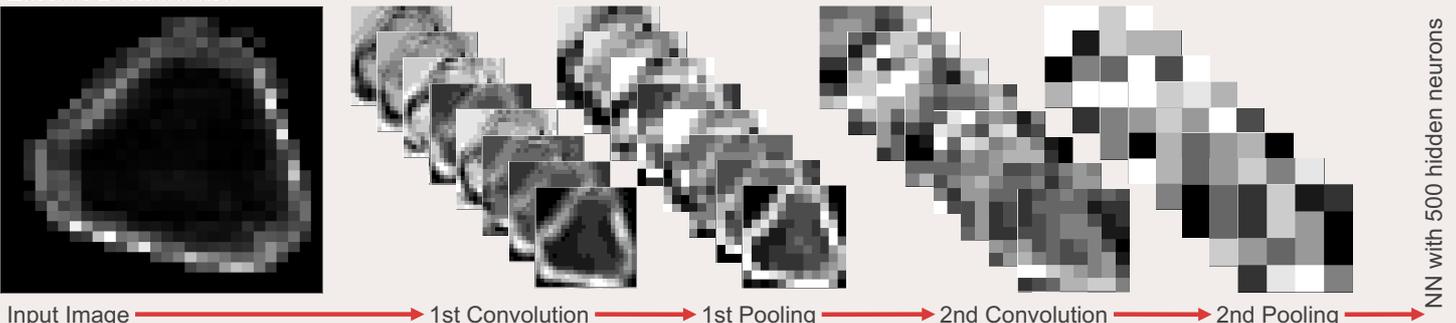
Inception bn	E. frax.	E. pauc.	E. p. niph.	E. stell.	Recall
E. frax.	71	10	7	5	76%
E. pauc.	7	65	7	10	73%
E. p. niph.	13	17	88	6	71%
E. stell.	9	9	2	79	80%

## Future

CNNs offer a promising tool in identifying pollen independent of predetermined morphological parameters, through their unique feature extraction and flexibility.



## LeNet Architecture



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## REFERENCES

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 Ioffe, S. and Szegedy, C. 2015. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167*.  
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## Feature extraction and Classification

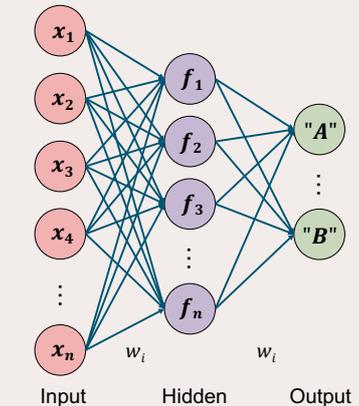
### Classifynder

The Classifynder extracted 50 features from the scanned images. Spanning simple geometric attributes, such as area, size, circumference, etc. and additional features aimed at capturing pollen surface structure and texture. These are fed into a Neural Network. During the training the data is split into two and trained separately.

### Convolutional Neural Networks

In CNNs the feature extraction is based on low level image manipulations (Kernel Convolutions) directly on the source images. The source images are turned into abstracted lower resolution versions through several convolution and pooling rounds. Every pixel from these features is treated as an input into a Neural Network.

## Neural Network Structure



**How Neural Networks work**  
 The neurons in the hidden layers are transforming inputs using activation functions (i.e sigmoid). During training the connection weights ( $w_i$ ) are adjusted to achieve the wanted result in the output layer.

